
Ayush Chopra
MIT
Cambridge, MA

Surya Kant Sahu
BIT
Durg, India

Abhishek Singh
MIT
Cambridge, MA

Abhinav Java
DTU
Delhi, India

Praneeth Vepakomma
MIT
Cambridge, MA

Vivek Sharma
MIT
Cambridge, MA

Ramesh Raskar
MIT
Cambridge, MA

ABSTRACT

Distributed deep learning frameworks like federated learning (FL) and its variants are enabling personalized experiences across a wide range of web clients and mobile/IoT devices. However, these FL-based frameworks are constrained by computational resources at clients due to the exploding growth of model parameters (e.g., billion parameter model). Split learning (SL), a recent framework, reduces client compute load by splitting the model training between client and server. This flexibility is extremely useful for low-compute setups but is often achieved at cost of increase in bandwidth consumption and may result in sub-optimal convergence, especially when client data is heterogeneous. In this work, we introduce AdaSplit which enables efficiently scaling SL to low resource scenarios by reducing bandwidth consumption and improving performance across heterogeneous clients. To capture and benchmark this multidimensional nature of distributed deep learning, we also introduce C3-Score, a metric to evaluate performance under resource budgets. We validate the effectiveness of AdaSplit under limited resources through extensive experimental comparison with strong federated and split learning baselines. We also present a sensitivity analysis of key design choices in AdaSplit which validates the ability of AdaSplit to provide adaptive trade-offs across variable resource budgets.

ACM Reference Format:
https://doi.org/10.1145/1122445.1122456

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Conference’17, July 2017, Washington, DC, USA
© 2018 Association for Computing Machinery.
ACM ISBN 978-1-xxxx-xxxx-x/YY/MM... $15.00
https://doi.org/10.1145/1122445.1122456

Figure 1: AdaSplit achieves improved accuracy under limited resources (bandwidth & compute) and can adapt to variable resource budgets. Results on Mixed-NonIID dataset.

1 INTRODUCTION

Distributed machine (deep) learning is characterized by a setting where many clients (web browsers, mobile/IoT devices) collaboratively train a model under the orchestration of a central server (e.g. service provider), while keeping the training data decentralized. As strict regulations emerge for data capture and storage such as GDPR [23], CCPA [77], distributed deep learning is being used to enable privacy-aware personalization across a wide range of web clients and smart edge devices with varying resource constraints. For instance, distributed deep learning is replacing third-party cookies in the chrome browser for ad-personalization [10, 20], enabling next-word prediction on mobile devices [29], speaker verification on smart home assistants [26], HIPPA-compliant diagnosis on clinical devices [68] and real-time navigation in vehicles [19].

A general distributed deep learning pipeline involves multiple rounds of training and synchronization steps where, in each round, a model is trained with local client data and updates across multiple clients are synchronized by the server into a global model. Techniques have been proposed with the goal to maximize accuracy under constraints on resource (bandwidth, compute) consumption. Figure 1 compares our proposed AdaSplit (in yellow) with strong baselines [27, 35, 49, 56, 79, 86] along these dimensions.

Federated learning (FL) [56] is one of the widely studied frameworks [12, 31, 49, 56, 86]. In each round of FL, first, all clients train a copy of the model locally on their device for several iterations.
and then, communicate the final model parameters with the server which synchronizes updates across clients by averaging all clients model parameters and shares back the unified global model for next training round. This is summarized in Figure 2. With entire model training on-client, federated learning is challenged by the compute budgets of client devices. First, on-client model training needs resource-intensive clients (with high-performance GPUs to avoid stragglers) and is increasingly becoming impractical due to exploding growth in model sizes (eg. billion parameter models for language and image modeling [17, 66, 89]). Second, as the number of clients (and/or model sizes) scales, bandwidth requirements for the system may worsen as entire models need to be communicated between client and server. Furthermore, at inference, often, storing the entire trained model on-client can have intellectual property implications that limit real-world usability.

More recently, the split learning (SL) framework [27, 65, 79, 82, 83] has emerged to alleviate some of these concerns in federated learning. SL reduces client computation load by involving the server in the training process. In each round, clients take turns to interact with the server for multiple iterations where they update parameters of a local model on the client and a (shared) global model residing on the server. Specifically, at each iteration, the client model generates input activations that are communicated to the server which uses them to compute gradients that are used to train the server model and transmitted to the client to train the client model. This is summarized in Figure 2. While client computation is significantly reduced in SL than FL, this comes at cost of an increase in client-server communication and often in-efficient convergence. First, since the client is dependent upon the server for training gradient, required communication budgets increase as the client interacts with the server in every iteration of a round (vs once-per-round in FL). This server is also blocked to train synchronously with each client. Second, since clients sequentially update shared parameters on the server, convergence may be in-efficient or sub-optimal, especially when client data is heterogeneous. Alleviating these concerns is the focus of this work.

We introduce AdaSplit, which enables split learning to scale to low-resource scenarios. First, a key insight in AdaSplit is to eliminate client dependence on server gradient which reduces communication cost and also enables asynchronous (and reduced) computation. Next, motivated by the fact that neural networks are vastly overparameterized, AdaSplit is able to improve performance by constraining heterogeneous clients to update sparse partitions of the server model. As shown in Figure 1, this enables AdaSplit to not only achieve improved performance under fixed resources (higher accuracy when similar bandwidth and compute) but also adapt to variable resource budgets (the trade-off curve). Furthermore, to capture and benchmark this multi-dimensional nature of distributed deep learning, we also introduce C3-Score, a metric to evaluate performance under resource budgets.

The contributions of this work can be summarized as:

- We introduce AdaSplit, an architecture for distributed deep learning that can adapt to and improve performance across variable resource constraints.
- We introduce C3-Score, a metric to benchmark and compare distributed deep learning techniques.
- We validate the effectiveness of AdaSplit through experiment comparison with state-of-the-art methods and sensitivity analysis of different design choices.

2 PRELIMINARIES AND MOTIVATION

First, we formalize the protocol and notation for the split learning (SL) framework. This is also visualized in Figure 2. For completeness, we also visualize the FL protocol in the same figure. While the training protocol may appear different, we unify their design choices along four key dimensions. Next, we formulate three key design dimensions and contextualize specific choices of FL and SL. This helps motivate our proposed AdaSplit technique.

2.1 Split Learning

Consider a distributed learning setup with N participating clients and 1 coordinating server. The key idea of split learning (SL) is to distribute (or split) the parameters of the training model across client and server. Each client i, for i ∈ [1, 2, ..., N] is characterized by a local client dataset Di, local client model Mi and a single server model M which is updated by all the clients. The training protocol is executed over R rounds of T iterations each. In each round, the N clients sequentially obtain access to interact with the server for model training over T iterations. In each iteration j (for j ∈ [1, 2, ..., T]) of client i updates the parameters of M and Mi. First, a mini-batch (xi, yi) is sampled from Di and passed through layers of client model Mi to generate activations ai = Mi(xi). In this document, we may refer to ai as split activations. Second, the pair of (ai, yi) is transmitted to the server. Third, at the server, ai is passed through layers of server model M to generate predictions yi = M(ai). The loss function L(yi, yî) is computed to generate gradients which are used to locally update parameters of M and then transmitted to the client to update parameters of Mi. In the classical setup, clients follow a round-robin mechanism where client i + 1 can start interacting with the server only after client i has completed its T iterations for the round. The global model is synchronized implicitly across clients by updating weights of the shared server model M. Furthermore, in some variants, clients models is transmitted between pairs of clients during a round [27] or averaged over all clients after the round ends [79]. Extensive work has been conducted to establish privacy in split learning and, while beyond scope of this paper, we briefly discuss that in Section 7.

2.2 Design Dimensions: 3C's

We define three key design dimensions which focus on how i) model is trained on local client data (Computation) and, ii) updates across the clients are synchronized, via the server, into a global model (Communication and Collaboration).

1. Computation: This governs how the processing of data at each client is executed between client and server. Hence, the computation cost can be defined as the total sum of floating-point operations (FLOPs) executed on the client and server. For N clients, this cost (C1) can be represented as:

\[ C1 \equiv \sum_{i=1}^{N} R \ast (F_{i}^{c} \ast T_{i}^{c} + F_{i}^{s} \ast T_{i}^{s}) \] (1)
Figure 2: Training protocols with N=3 clients for federated learning (FL), split learning (SL) and our proposed AdaSplit which builds upon split learning framework. AdaSplit improves i) Computation using the local client gradient (with $I_{\text{client}}$) and training the server intermittently (using gate $G(.)$ parameterized by $\kappa$), ii) Communication by reducing payload size (no gradient flow from server-client) and interaction frequency (using $O(.)$ parameterized by $\eta$) and iii) Collaboration by allowing each client to update sparse partition of server parameters (on edges with active gradient flow). Specifically, in this figure, client (b) is in local phase and client (a,c) are in global phase. Client (a) is selected to train and it only updates a sparse partition of server model parameters corresponding to edges with active gradients on the server. The protocol is detailed in Section 3.

where, $F^c_i$ are the FLOPs executed on client for $T^c_i$ iterations, $F^s_i$ are FLOPs executed on server for $T^s_i$ iterations when training with data for client $i$ and $R$ is number of rounds. $F^c_i$ and $F^s_i$ increase (or decrease) monotonically with increase (or decrease) in size of client model $M_i^c$ and server model $M^s$ respectively. In federated learning, $F^c_i = 0$ and $T^s_i = 0$ since the entire model is executed on client device ($M^s = 0$). In contrast, split learning allows to split the model and distribute $F_s$ and $F_c$ between client and server, based on resource availability. This flexibility of split learning allows scaling to low-resource setups where clients are compute constrained (but servers may scale horizontally) and is a key aspect for design of AdaSplit. However, we also note that this classical split learning framework increases compute load on the server and also blocks the server to train synchronously with each client.

2. Communication: This governs how client-and-server interact with each other. Hence, the communication cost can be defined as the total payload that is transmitted between each of the $N$ client-server pairs over multiple rounds of training. Federated and Split Learning differ based on the modality of the payload and frequency of interaction. However, without loss of generality, this cost ($C_2$) can be represented as:

$$C_2 = \sum_{i=1}^{N} \sum_{j=1}^{R} \sum_{k=1}^{T} (P_{is} + P_{si}) \cdot \sigma(i, j, k)$$

where $N$ is number of clients, $R$ is training rounds and $T$ is iterations per round. $P_{is}$ is the payload transmitted from a given client $i$ to server $s$ and $P_{si}$ is the payload transmitted from server $s$ to client $i$. $\sigma(i, j, k)$ denotes if client $i$ interacts with server during iteration $k$ of round $j$. In federated learning, client-server interact using model weights once-per-round. Hence, size of each $P_{is}$, $P_{si}$ is size of the total model and $\sigma(i, j, k) = 1$ only for $k = T$ (last iteration of every round). In split learning, $P_{is}$, $P_{si}$ is size of a batch of activations and gradients respectively and $\sigma(i, j, k) = 1$ Vi, j, k since client depends upon server for gradient. We note that, even though size of the payload is relatively smaller for split learning (one activation batch vs full model), the high frequency of communication may result in more bandwidth consumption than federated learning.

3. Collaboration: This governs how learning (or updates) from local data across the clients is synchronized in the global model. Unlike communication and computation, the cost is non-trivial to define but the impact is measured from the converged accuracy. If the client datasets $D_i$ for $i \in \{1, 2, ..., N\}$ could be centralized, the unified dataset $D = D_1 \cup D_2 \cup \cdots \cup D_N$ can be used to train a performant model with gradient descent by sampling iid batches $b \sim D$. Federated and split learning require mechanisms to achieve convergence when this data is decentralized. Abstractly, federated learning executes this by averaging client model parameters (or gradients) on the server after each round, and split learning executes this by requiring all clients to (sequentially) update shared parameters of the server during the round.

In federated training, the global model in a round $r$ and consequently updated client models ($M^c_i$) are obtained as:

$$M^g = \sum_{i=1}^{N} (M^c_i \cdot p^r_i)$$

$$M^c_i = M^g \forall i \in \{1, 2, ..., N\}$$

where $p^r_i$ is a weight assigned to client $i$ in round $r$. 
In split training during each round $r$, the server model ($M_s$) is updated sequentially by all client $i$ for $i \in [1, 2, ..., N]$ as:

$$M_s^r = M_s^r - \alpha \cdot \nabla \mathcal{L}(M_s^r, y_i)$$  (4)

In some variants of split learning such as [79], local client models may also synchronized, at end of each round, similar to federated learning using equation 3. Then, the global model is obtained by stacking the server and client models. We note that when data across clients are non-iid (that is common on real-world distributed setup), inefficient or sub-optimal converged accuracy is observed in $M_s^r$. In split learning, we posit that this happens since gradients from non-iid activations sequentially update the same parameters which violates assumptions of empirical risk minimization [81].

3 ADASPLIT

In this section, we delineate the design choices of AdaSplit along each of the three dimensions. We also discuss corresponding trade-offs that enable AdaSplit to adapt to variable resource constraints. Unless specified otherwise, we follow the same notation as defined in Section 2. The architecture is visualized in Figure 2.

3.1 Computation

The training model is split between the client and server. Following split learning, each client is characterized by a local client model $M_i^r$ and a global server model $M_s$ that is shared across all clients. This flexibility to distribute the model allows scaling split learning (and AdaSplit) to low resource setups. Recall from Section 2.2, that in classical split learning, this increases computation load on the server and also blocks the server to train synchronously with each client model which depends upon the server for the gradient.

AdaSplit alleviates these concerns by i) eliminating the dependence of the client model on server gradient and ii) only training the server intermittently. This further lowers the total computation cost by decreasing $T_s$ (compute iterations on the server) and also unblocks the server to execute asynchronously from the client.

Local Client Gradient: First, AdaSplit generates the gradient for training client model on-client itself using a local objective function $L_{\text{client}}$ which is a supervised version of NT-Xent Loss [76]. Given an input batch, $b \sim D_i$, then for each input $(x_i, y_i) \sim b$, $L_{\text{client}}$ is applied on a projection $(H(.) )$ of the activations $a_i$ generated by the client model ($= M_i^r(x_i)$). Let $q_i = H(a_i)$ be the corresponding embedding of input $x_i$, and $Q_i$ be the set of embeddings of other inputs with the same class as $x_i$ in the batch $b$, the loss can be represented as below:

$$L_{\text{client}} = \sum_{i=0}^{||b||} \sum_{q_i \in Q_i} - \log \frac{\exp(q_i \cdot q_s / \tau)}{\sum_{j \neq i} \exp(q_i \cdot q_j / \tau)}$$  (5)

Here, $\tau$ is a hyperparameter, which controls the “margin” of closeness between embeddings. We set $\tau = 0.07$ in all our experiments. The pairs (anchor $q_i$, positive inputs $q_s$) required in $L_{\text{client}}$ are sampled using the ground truth labels ($y_i$) locally on client.

Intermittent Server Training: Second, AdaSplit also splits the $R$ round training into two phases: A) Local Phase B) Global Phase. Local Phase lasts for the first $\kappa$ rounds when only the client model trains, asynchronously and without interacting with the server, using $L_{\text{client}}$. After $\kappa$ rounds (till end), the Global Phase starts where client interacts with the server by transmitting activations. The server model only now start training on data from the clients. The server model $M_s$ is optimized using a server loss function ($L_{\text{server}}$) which is cross-entropy ($L_c$) for classification tasks. We note that, even in global phase, client model continues to train using $L_{\text{client}}$ and does not receive any gradient from the server.

Essentially in AdaSplit, client models leverage compute resources of the server only when required. AdaSplit can adapt to variable computation budgets by regulating two key hyperparameters: i) size of the client model ($\mu$) for (client compute), ii) duration of local phase ($\kappa$) for (server compute). We study the specific impact of these design choices in Section 6. Also, in practice, we observe considerable reductions in total computation since $\kappa$ can assume large values ($0.8 R$), where $R$ is total training rounds, without significant loss of performance. We corroborate this with results in Section 5.

3.2 Communication

Recall from Section 2.2 that in classical split learning, the high client-server interaction can be prohibitive for communication cost. AdaSplit alleviates this problem by i) decreasing the payload size and ii) the frequency of communication.

Smaller Payload: First, we note that eliminating client dependence on server gradient also significantly reduces communication cost, apart from decreasing computation. In AdaSplit, $P_{si} = 0$ (from equation 2 in Section 2.2) throughout training for each client $i$. Through sensitivity analysis in Section 6, we validate that this design choice marginally drops the performance while significantly reducing communication.

Infrequent Transmission: Second, we note that two-phase training is also beneficial for communication. In the Local Phase, there is no client-to-server communication, with the payload $P_{is} = 0$ for all clients $i$ (from equation 2 in Section 2.2). In the Global Phase, clients may start transmitting activations to the server. In this phase, only a subset of clients communicates with the server in each round. Specifically, we introduce an Orchestrator ($O$) which resides on the server and uses a running statistic of local client losses to select (\eta N) clients in each iteration, that communicate with the server. In AdaSplit, $O$ uses a UCB [2] strategy to prioritize clients who need the server model to improve performance on their data (exploitation) while also ensuring that the final model can generalize well to different client data distributions (exploration).

Let $S_i^t$ is a binary flag denoting if client i is selected at iteration $t$ and $L_i^t$ denotes the server loss from activations ($a_i$) for the iteration. At each iteration $t$, selected clients (i.e. $S_i^t = 1$) transmit input activations to update server model and the loss $L_i^t$ is stored. For unselected clients (i.e. $S_i^t = 0$), $L_i^t$ is defined the average of their loss value in previous iterations ($L_i^t = \frac{t_i^{t-1} + t_i^{t-2}}{2}$). Here, we note that $L_i^t$ is only used for selection and the client model continues to train locally with $L_{\text{client}}$. Finally, $O$ assigns a new score to each client using the advantage function and clients with the top-$\eta$ scores are selected for next iteration. The advantage function ($A_t$) for [2] is defined below:

$$A_i = \frac{l_i}{s_i} + \sqrt{\frac{2 \log T}{s_i}}$$  (6)
where, \( l_i = \sum_{y=0}^{T-1} y^{T-1-t} \cdot L_i^t, s_i = \sum_{y=0}^{T} Y^{T-1} \cdot S_i^t \) and \( T \) is total iterations in the round. \( y \in [0, 1] \) is a hyperparameter that determines the importance of historical losses. We initialize \( L_i^0 = 100 \) for all clients for \( t = 0 \) and \( t = 1 \).

Before proceeding, we make a few statements here. First, we note that subset selection has previously been used in FL to regulate communication cost \([14, 49, 56]\) where the global model after a round may be obtained from few clients only (see variable \( p_i^f \) in equation 3). However, classical split learning does not have a similar infrastructure since each client is entirely dependent on the server for gradient during training. Eliminating client dependence on server gradient in AdaSplit helps realize the benefit. Finally, we highlight that the design of orchestrator is specialized for AdaSplit where it needs to be invoked in each iteration (vs rounds in FL) and selects client for training (vs model averaging in FL).

AdaSplit can adapt to variable communication budgets by regulating two key hyperparameters: i) the number of selected clients (\( \eta \)), ii) the duration of the local phase (\( \kappa \)). We study the specific impact of these design choices in Section 6. In practice, we observe considerable reductions in communication cost since \( \kappa, \eta \) can assume large values (\( \kappa = 0.8 \ast \iota, \eta = 0.6 \ast \iota \)) without significant loss of performance. We corroborate this with results in Section 5.

### 3.3 Collaboration

AdaSplit, like split learning, synchronizes updates in the global model by requiring clients to sequentially update shared server model parameters. Recall from Section 2.2 that when inter-client data is heterogenous, this often results in the global model converging to sub-optimal accuracy. To alleviate this, the key idea in AdaSplit is to have each client update only a partition of the server model (\( M_a \)) parameters. The motivating insight is to take advantage of the fact that neural network models are vastly over-parameterized \([59]\) and only a small proportion of the parameters can learn each (client’s) task with little loss in performance \([24, 43, 52, 78]\).

#### Update Sparse Partitions of Server Model: During the global phase, we add an \( L^1 \) weight regulator to promote sparsity in the server model \( M^t \). Specifically, instead of pruning the network, we learn a client (i) specific multiplicative mask \( m_i \) which constrains the set of \( M^t \) parameters client \( i \) can update. Given batch of activations \( a_i \) from client \( i \), server model \( M^t \) is updated as:

\[
M^t = M^t - \alpha \ast m_i \ast \nabla \hat{L}(M^t(a_i), y_i)
\]

This simulates relative sparsity (for each client) in \( M^t \) without pruning any parameters since goal is to increase server model capacity (to accommodate many diverse clients) rather than achieving compression. Here, \( m_i \) evolves during training and is forced to be extremely sparse by optimizing the following objective on the server for each client \( i \):

\[
L_{server} = L_{ce}(y_i, y_i) + \lambda \ast \omega(m_i)
\]

where, \( \omega(.) \) is an \( L^1 \) regularizer and \( \hat{y}_i = M^t(M_i(x_i)) \). The \( \lambda \) hyperparameter promotes sparsity of the masks and can be intuitively visualized as controlling the extent of collaboration between clients on the server. At inference, the effective server model for client is \( M^t \ast m_i \) where \( m_i \) is a highly sparse binary mask and may be stored on client. Results in Section 5 show that this strategy of regulating collaboration significantly improves performance. Finally, we note similarities between each round of collaboration in AdaSplit and continual learning, albeit AdaSplit works in activation space and is iterative. However, we anticipate exploring this connection may present interesting directions of future work.

### 4 EXPERIMENTAL SETUP

First, we formalize the experimental protocol with datasets and baselines. Next, we define the evaluation protocol and introduce the \textit{C3-Score} as a unified metric to benchmark and compare the efficiency of distributed deep learning techniques. Finally, we summarize implementation details for results presented in this work.

#### 4.1 Datasets
To robustly validate the efficacy of AdaSplit, we conduct extensive experiments on benchmark datasets and simulate varying levels of inter-client heterogeneity. Specifically, we design two experimental protocols, as described next: a) **Mixed-CIFAR**: We divide the 10 classes of CIFAR-10 \([40]\) into 5 subsets of 2 distinct classes each. Every client is assigned data from one of the 5 subsets. In this protocol, there is low and consistent heterogeneity between data across all pairs of clients. b) **Mixed-NonIID**: We use 5 benchmark datasets: i) MNIST \([42]\) ii) CIFAR-10 \([40]\) iii) FMNIST \([88]\) iv) CIFAR-100 \([40]\) v) Not-MNIST \([9]\) and each client receives samples from exactly one dataset. In this protocol, there is high and variable inter-client heterogeneity between client pairs. For instance, clients with FMNIST and MNIST have lower pairwise-heterogeneity between each other and high pairwise heterogeneity with clients containing CIFAR-100. For experiments with both protocols, input images are scaled to 32x32x3 and greyscale MNIST/FMNIST images are transformed by stacking along channels. We will release the evaluation protocol with the code for use by the research community.

#### 4.2 Baselines
We compare state-of-the-art split learning and federated learning techniques. Specifically, for split learning, we compare with SL-basic \([27]\) and SplitFed \([79]\). To ensure validity of analysis and also highlight efficacy of results, we also compare with state-of-the-art federated learning techniques: FedAvg \([56]\), FedNova \([86]\), Scaffold \([35]\) and FedProx \([49]\). These techniques are specially designed for heterogenous (non-iid) setups and provide strong benchmarking for the efficacy of AdaSplit.

#### 4.3 Evaluation Metrics: C3-Score
We evaluate performance both independently along each of the dimensions as well as using a unified metric. To evaluate along design dimensions, we report \textit{Accuracy}, \textit{Bandwidth} and \textit{Compute}. Accuracy is measured as mean and standard deviation over multiple independent runs with different seeds. Bandwidth is measured in GB and Compute is measured in TFLOPS. We note that, in real-world cases, servers may scale horizontally and bottleneck is often at client. For completeness, we report both client compute and total (client+server) compute.

**C3-Score**: For an efficient method, the goal is to maximize accuracy while minimizing resource (bandwidth, compute) consumption. We introduce \textit{C3-score}, a metric to evaluate joint performance of any distributed deep learning technique in this multi-dimensional

Table 1: Results on Mixed-CIFAR dataset. AdaSplit achieves improved performance while reducing resource (bandwidth, compute) consumption. This is corroborated by the C3-Score (higher is better).

<table>
<thead>
<tr>
<th>Method</th>
<th>Accuracy</th>
<th>Bandwidth (GB)</th>
<th>Compute (TFLOPS)</th>
<th>C3-Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>SL-basic [27]</td>
<td>84.65 ± 0.32</td>
<td>84.54</td>
<td>3.76 (15.14)</td>
<td>0.72</td>
</tr>
<tr>
<td>SplitFed [79]</td>
<td>84.67 ± 0.24</td>
<td>84.64</td>
<td>3.76 (15.14)</td>
<td>0.73</td>
</tr>
<tr>
<td>FedAvg [56]</td>
<td>82.21 ± 0.19</td>
<td>2.39</td>
<td>17.13 (17.13)</td>
<td>0.72</td>
</tr>
<tr>
<td>FedProx [49]</td>
<td>85.09 ± 0.29</td>
<td>2.39</td>
<td>17.13 (17.13)</td>
<td>0.75</td>
</tr>
<tr>
<td>Scaffold [35]</td>
<td>84.73 ± 0.17</td>
<td>4.78</td>
<td>17.13 (17.13)</td>
<td>0.74</td>
</tr>
<tr>
<td>FedNova [86]</td>
<td>82.71 ± 0.27</td>
<td>2.39</td>
<td>17.13 (17.13)</td>
<td>0.73</td>
</tr>
<tr>
<td>AdaSplit (κ=0.6, η=0.6)</td>
<td>88.88 ± 0.27</td>
<td>9.71</td>
<td>5.38 (8.82)</td>
<td>0.85</td>
</tr>
<tr>
<td>AdaSplit (κ=0.75, η=0.6)</td>
<td>87.11 ± 0.59</td>
<td>2.43</td>
<td>5.38 (10.88)</td>
<td>0.83</td>
</tr>
</tbody>
</table>

Table 2: Results on Mixed-NonIID dataset. AdaSplit achieves improved performance while reducing resource (bandwidth, compute) consumption. This is corroborated by the C3-Score (higher is better).

<table>
<thead>
<tr>
<th>Method</th>
<th>Accuracy</th>
<th>Bandwidth (GB)</th>
<th>Compute (TFLOPS)</th>
<th>C3-Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>SL-basic [27]</td>
<td>67.90 ± 3.52</td>
<td>34.88</td>
<td>1.66 (13.76)</td>
<td>0.59</td>
</tr>
<tr>
<td>SplitFed [79]</td>
<td>71.46 ± 2.13</td>
<td>35.94</td>
<td>1.66 (13.76)</td>
<td>0.62</td>
</tr>
<tr>
<td>FedAvg [56]</td>
<td>91.31 ± 0.49</td>
<td>2.39</td>
<td>11.77 (11.77)</td>
<td>0.79</td>
</tr>
<tr>
<td>FedProx [49]</td>
<td>92.54 ± 0.48</td>
<td>2.39</td>
<td>11.77 (11.77)</td>
<td>0.81</td>
</tr>
<tr>
<td>Scaffold [35]</td>
<td>87.30 ± 1.36</td>
<td>4.79</td>
<td>11.77 (11.77)</td>
<td>0.76</td>
</tr>
<tr>
<td>FedNova [86]</td>
<td>88.94 ± 0.32</td>
<td>2.39</td>
<td>11.77 (11.77)</td>
<td>0.77</td>
</tr>
<tr>
<td>AdaSplit (κ=0.6, η=0.6)</td>
<td>91.92 ± 1.88</td>
<td>2.85</td>
<td>2.38 (4.81)</td>
<td>0.89</td>
</tr>
<tr>
<td>AdaSplit (κ=0.3, η=0.6)</td>
<td>92.91 ± 0.91</td>
<td>6.57</td>
<td>2.38 (6.63)</td>
<td>0.88</td>
</tr>
</tbody>
</table>

4.4 Implementation Details

All experiments are trained for (R=20) rounds with 1 epoch per round using the same convolutional (LeNet) backbone. Results are reported for 5 (=N) clients. For the federated learning baselines, we use open-source implementations provided in [48]. For robust comparison, we also tuned parameters for these baselines and note some performance gain was observed (over default values) which is then used for comparison. For all split learning baselines, we set the default client model size is 20% (µ = 0.2) and use Adam optimizer with a learning rate of 1e-3. This same optimizer configuration is used for both client and server loss in AdaSplit. In AdaSplit, the default parameters are: a) κ = 0.6, η = 0.6, γ = 0.87, λ = 1e-5 (for Mixed-CIFAR) and 1e-3 (for Mixed-NonIID). For experiments on Mixed-CIFAR and Mixed-NonIID, the communication and computation budgets are chosen to be the performance of worst-performing baselines on the corresponding dataset respectively. Experiments are implemented in Pytorch, executed on 1 NVIDIA RTX-3060 GPU and reported over 5 independent runs.

5 RESULTS

We report performance on Mixed-CIFAR in Table 2 and Mixed-NonIID in Table 1. For C3-Score, we set the bandwidth and communication budgets to be Bmax = 35.94 GB and Cmax = 11.77 TFLOPS on Mixed-CIFAR and Bmax = 84.64 GB and Cmax = 17.13 TFLOPS on Mixed-NonIID. These values correspond to the highest bandwidth and computation cost among all the methods for the corresponding datasets. The results on both datasets consistently support the following key observations:

1. AdaSplit outperforms other split learning techniques and achieves significantly better accuracy while also reducing bandwidth consumption. For instance, on Mixed-CIFAR (Table 2), in comparison to SL-basic, AdaSplit improves performance by 24% and consumes 89% lower bandwidth. This is corroborated by an increase in C3-Score from 0.59 for SL-basic [27] to 0.89 for AdaSplit. Furthermore, similar trend is observed on Mixed-NonIID (Table 1) as well. Specifically, AdaSplit achieves accuracy of 88.88 against
We observe that we note marginal gain in performance for larger server model since with the number of client layers. We also observe a decrease in (2.39 GB). This is corroborated with an improved C3-Score of 0.85 with the closest fed-erated learning baseline (FedProx) [49] at 0.81, FedAvg [56] at 0.79 and SplitFed at 0.62. Furthermore, similar trend is observed on Mixed-NonIID as well. Specifically, AdaSplit achieves a C3-Score of 0.85 with the closest baseline FedProx at 0.75, Scaffold [35] at 0.74 and SL-basic [27] at 0.72. 

AdaSplit can adapt to variable resource budgets. From results on Mixed-NonIID (Table 5), we can see that given a higher communication budget (13.36 GB), AdaSplit can further improve accuracy to 89.77% which corresponds to a 5% improvement over FedProx [49]. Figure 1 shows trade-offs that AdaSplit can achieve for accuracy by varying bandwidth (and compute) budget. We note that the respective trade-off curves for bandwidth (and compute) are obtained while keeping compute (and bandwidth) budgets fixed respectively. We discuss in more detail in Section 6.

### 6 DISCUSSION

In this section, we conduct a sensitivity analysis of key design choices in AdaSplit and analyze the consequent impact on accuracy and resource consumption. Results validate the ability of AdaSplit to efficiently adapt to variable resource budgets. Unless specified otherwise, the hyperparameters used are \( \alpha = 0.6, \eta = 0.6, \mu = 0.2 \).

1. **Varying Size of Client Model**: Table 3 presents results from varying number of layers on client for Mixed-CIFAR10 dataset. We observe that Communication on client increases monotonically with the number of client layers. We also observe a decrease in Communication cost as evident from lower bandwidth. This can be attributed to the convolution design of the model where split activations becomes smaller with depth (reducing payload \( P_{ij} \)). Also, we note marginal gain in performance for larger server model since it provides more parameters for Collaboration. We observe similar trends on Mixed-NonIID and include results in the appendix. Hence, AdaSplit adapts to variable client computation budgets.

2. **Varying Duration of Local Phase**: Table 4 presents results from varying \( \kappa \) on Mixed-CIFAR10 dataset. We observe that Communication cost decreases as \( \kappa \) increases. This is because \( P_{ij} = 0 \) for all rounds \( r < \kappa \) on given client \( i \). Communication cost of the server also decreases on increasing \( \kappa \) though client compute is unchanged. We note marginal decrease in accuracy since higher \( \kappa \) allows for fewer collaboration iterations on server. Specifically, increasing \( \kappa \) from 0.3 to 0.9 decrease accuracy from 89.80% to 87.11%, while bandwidth falls drastically from 17.22 GB to 2.43 GB. This is corroborated on Mixed-NonIID as shown in Table 5. Hence, AdaSplit adapts to variable communication and server computation budgets.

3. **Eliminating Gradient Dependence**: Table 5 studies the impact of training client model without gradient from server on Mixed-CIFAR10 dataset. We observe Communication cost decreases significantly with bandwidth reduced by one-half. We observe accuracy is generally insensitive though there is slight increase in standard deviation. Hence, AdaSplit adapts to variable communication budget and provides consistent performance.

4. **Further Reducing Payload Size**: While we sparsify server model parameters to improve collaboration in AdaSplit, here we also consider sparse sparsity of split activations to reduce communication payload. Specifically, we train the client model with an additional \( L^1 \) regularizer that regulates magnitude of split activations. Results are presented on Mixed-NonIID in Table 6. Communication remains unchanged. Communication decreases as payload \( P_{ij} \) becomes sparse. This results in fall in accuracy which highlights worsening collaboration. For instance, AdaSplit can train with only 0.76 GB of bandwidth and achieve 85.79% accuracy. From Table 1, FedProx achieves 85.09% and consumes 2.39 GB budget. Hence, AdaSplit adapts to extremely low communication budgets.

### 7 RELATED WORK

In this section, we review the literature in distributed and collaborative deep learning broadly, and specific research in split learning.

**Parallelizable Deep Learning.** For centralized machine learning, some parallelization methods have been proposed to enable training on large-scale data sources. Data Parallelism [33] based distributed ML simulates large mini-batch training by splitting data among multiple identical models and training each model on a shard of the data independently. The key challenge is to ensure consistency of the global model by synchronizing across multiple model copies. This is achieved via i) Synchronous Optimization - which synchronizes after every minibatch [11, 15], resulting in high

<table>
<thead>
<tr>
<th>( \kappa )</th>
<th>Accuracy</th>
<th>Bandwidth (GB)</th>
<th>Compute (TFLOPS)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.3</td>
<td>92.91 ± 0.91</td>
<td>6.57</td>
<td>2.38 (6.63)</td>
</tr>
<tr>
<td>0.45</td>
<td>90.97 ± 1.02</td>
<td>4.72</td>
<td>2.38 (5.72)</td>
</tr>
<tr>
<td>0.6</td>
<td>89.77 ± 1.62</td>
<td>3.56</td>
<td>2.38 (4.81)</td>
</tr>
<tr>
<td>0.75</td>
<td>88.62 ± 3.68</td>
<td>2.15</td>
<td>2.38 (3.90)</td>
</tr>
<tr>
<td>0.90</td>
<td>88.02 ± 0.91</td>
<td>0.89</td>
<td>2.38 (2.98)</td>
</tr>
</tbody>
</table>

Table 4: Results on Mixed-CIFAR10. Varying duration of local phase (\( \kappa \)) enables AdaSplit to adapt to variable communication budget.
Table 5: Results on Mixed-NonIID. In each Accuracy cell, Row-1 trains client with $L_{\text{client}}$, and Row-2 trains client with $L_{\text{client}} + L_{\text{server}}$. Accuracy is largely insensitive to server gradient across various $\kappa$.

<table>
<thead>
<tr>
<th>$\kappa$</th>
<th>Accuracy</th>
<th>Bandwidth (GB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.3</td>
<td>89.80 ± 0.38</td>
<td>17.22</td>
</tr>
<tr>
<td></td>
<td>89.96 ± 0.23</td>
<td>34.84</td>
</tr>
<tr>
<td>0.45</td>
<td>89.77 ± 0.34</td>
<td>13.36</td>
</tr>
<tr>
<td></td>
<td>89.47 ± 0.21</td>
<td>27.18</td>
</tr>
<tr>
<td>0.60</td>
<td>89.08 ± 0.38</td>
<td>9.65</td>
</tr>
<tr>
<td></td>
<td>89.03 ± 0.28</td>
<td>19.79</td>
</tr>
<tr>
<td>0.75</td>
<td>88.17 ± 0.59</td>
<td>6.10</td>
</tr>
<tr>
<td></td>
<td>88.31 ± 0.40</td>
<td>12.06</td>
</tr>
<tr>
<td>0.90</td>
<td>87.11 ± 0.45</td>
<td>2.43</td>
</tr>
<tr>
<td></td>
<td>87.05 ± 0.39</td>
<td>4.89</td>
</tr>
</tbody>
</table>

Table 6: Results on Mixed-CIFAR10 dataset. Sparsification of split activations enables AdaSplit to adapt to extremely low communication budgets.

<table>
<thead>
<tr>
<th>$\beta$</th>
<th>Accuracy</th>
<th>Bandwidth (GB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>91.09 ± 1.48</td>
<td>3.45</td>
</tr>
<tr>
<td>1e-7</td>
<td>90.52 ± 2.16</td>
<td>3.25</td>
</tr>
<tr>
<td>1e-6</td>
<td>91.92 ± 1.89</td>
<td>2.85</td>
</tr>
<tr>
<td>5e-6</td>
<td>87.64 ± 4.82</td>
<td>1.19</td>
</tr>
<tr>
<td>1e-5</td>
<td>85.79 ± 4.10</td>
<td>0.76</td>
</tr>
<tr>
<td>0.0001</td>
<td>79.18 ± 4.81</td>
<td>0.08</td>
</tr>
<tr>
<td>0.1</td>
<td>51.00 ± 0.42</td>
<td>0.0044</td>
</tr>
</tbody>
</table>
been explored such as communication [75], healthcare applications [22], privacy [36], IoT [21] and frameworks [85]. Several recent works have integrated federated and split learning architectures such as SplitFed [79], SplitFedV3 [22] and FedSL [1]. In addition to the computational and communication benefit, split learning allows distributed and privacy-preserving prediction that is not possible under the federated learning framework. Consequently, several works have used split learning for inference to build defense [7, 45, 50, 57, 61, 69, 70, 74, 87] and attack mechanisms [32, 53, 64]. Some of these benefits have led to applied evaluation of split learning for mobile phones [62], IoT [37, 38, 63], model selection [71, 72] and healthcare [65].

8 CONCLUSION

We introduce AdaSplit, a technique for scaling distributed deep learning to low resource scenarios. AdaSplit builds upon the split learning framework and reduces a) computation by eliminating client dependence on server gradient and training the server intermittently, b) bandwidth by reducing payload size and communication between client-and-server, and c) improves performance by constraining each client to update sparse partitions of server model. To capture and benchmark this multi-dimensional nature of distributed deep learning, we also introduce C3-Score, a metric to evaluate performance under resource budgets. We validate the effectiveness of AdaSplit under limited resources through extensive experimental comparison with strong federated and split learning baselines. We also present sensitivity analysis of key design choices in AdaSplit which validates the ability of AdaSplit to provide adaptive trade-offs across variable resource budgets.

REFERENCES


